Mining Users' Opinions based on Item Folksonomy and Taxonomy for Personalized Recommender Systems

Huizhi Liang
Faculty of Science and Technology
Queensland University of Technology
Brisbane, Queensland, Australia
oklianghuizi@gmail.com

Yue Xu
Faculty of Science and Technology
Queensland University of Technology
Brisbane, Queensland, Australia
yue.xu @qut.edu.au

Yuefeng Li
Faculty of Science and Technology
Queensland University of Technology
Brisbane, Queensland, Australia
y2.li @qut.edu.au

***Abstract*—Item folksonomy or tag information is a kind of typical and prevalent web 2.0 information. Item folksonmy contains rich opinion information of users on item classifications and descriptions. It can be used as another important information source to conduct opinion mining. On the other hand, each item is associated with taxonomy information that reflects the viewpoints of experts. In this paper, we propose to mine for users' opinions on items based on item taxonomy developed by experts and folksonomy contributed by users. In addition, we explore how to make personalized item recommendations based on users' opinions. The experiments conducted on real word datasets collected from Amazon.com and CiteULike demonstrated the effectiveness of the proposed approaches.**

Keywords-Recommender Systems; Folksonomy; Tags; Opinion Mining; Personalization; Taxonomy

I. INTRODUCTION

Recommender system is an effective tool to deal with the issue of information overload. Besides the typical explicit ratings, in Web 2.0, users' explicit textural information such as tags, blogs, reviews and comments becomes popular. Instead of using numeric numbers, people use one or more pieces of textural information to express their opinions and interest, collect and organize items, share experiences, and build up social networks. How to mine users' opinions based on these kinds of user created textural information and then recommend items to users becomes very important. Currently, mining users' sentimental orientations to items based on reviews, blogs and comments are the major focus of opinion mining [3]. Since tags are mainly keywords instead of sentences, usually it is difficult to conduct opinion mining using the traditional sentimental analysis approaches.

However, we argue that tags can be used as another important information source to profile users' opinions. Different from reviews, blogs and comments that expressing users' sentimental orientation to items, tags express users' opinions on item classifications and descriptions. For example, for the book "The World is Flat", assume user u_1 labeled it with a tag "globalization" while user u_2 described it with a tag "outsourcing". The two tags not only reflect their topic interests or preferences [6], but also reflect these people's different opinions for the classifications and descriptions of this item [4]. Another kind of opinion information that contained in tags is that if a set of items are put together by one user, then, these items are similar or closely related in the opinion of that user. Therefore, tags contain rich opinion information.

Besides folksonomy that expresses users' opinions on item classifications, each item is associated with item taxonomy that reflects experts' viewpoint on item classification and descriptions, for example, the product classification taxonomy of Amazon.com, and world knowledge ontology such as Library of Congress Subject Headings [12]. Because item taxonomy has the advantages of having standard and controlled vocabulary, independent with user communities and being well recognized as common knowledge, it can be used to reduce the noise of tags [7] and profile users' opinions on items.

Currently, the rich opinion information in folksonomy is ignored. Some pioneer work discussed how to hybrid taxonomy and folksonomy for knowledge organization [2], and navigation [15]. The existing recommender systems only used one of the two information sources. For example, the recommendation approaches based on item taxonomy [8] or tags [6]. In this paper, we propose to use the rich opinion information on item classification and description based on both item folksonomy and taxonomy to make item recommendations.

Tags and taxonomic topics are categories which represent various conceptual aspects of the items so that users can classify items into these categories according to their opinions or understanding to the items. Thus the tags and taxonomic topics can be considered representing different features of items. In this paper, we propose to use tags and taxonomic topics as the features of items. Different from the typical "negative", "neutral" and "positive" values, we use the numeric value ranging from 0 to 1 to express users' opinions on the features. The higher the value, the more the user agrees that the item can be described with the feature.

This paper is organized as follows. Firstly, the related work is briefly reviewed in Section II. Then, some important notations are given in Section III. The proposed approaches are discussed in details in Section IV. Firstly, the approaches of mining users' opinion on items are presented and then, the collaborative filtering recommendation approaches based on users' opinions are discussed. In Section V and VI, the design of the experiments, experimental results and discussions are presented. The conclusions and future work are discussed in Section VII.

II. RELATED WORK

Opinion mining is an important research area. The techniques of text mining, natural language processing and sentiment analysis are employed to find users' opinions [3]. The major tasks of opinion mining include mining the features of items and finding the users' sentimental orientations to the features or items [3]. Some opinion mining approaches based on users' reviews [13], blogs [11] and forum posts are proposed. Traditionally, recommender systems operate based on user-behavior and rating data [14]. How to incorporate users' opinions in recommender system arouses attentions [14]. For example, the work [10] discussed how to improve the recommendation accuracy through combining the opinion information contained in users' reviews and the explicit ratings. However, how to use the rich opinion information of tags to make recommendation still remains an open research question.

Currently, the recommendation approaches based on tags are mainly focus on how to recommend tags to users [16]. Not so much work has been done on the item recommendations based on tags. Since recommending a tag to a user to label an item is different with recommending an item to a user, the tag recommendation approaches usually cannot be used to recommend items directly [16]. The current approaches ignored the rich opinion information in tags. How to make use of the rich opinion information of folksonomy to improve the accuracy of item recommendations still need to be further investigated.

Item taxonomy is one important traditional information source to profile users [1]. The important recommendation approaches based on item taxonomy include the work [8] and [17]. The work [8] proposed an approach to take the structural information of item taxonomy to make personalized item recommendations. The work [17] proposed to combine the implicit and explicit item preferences, with the topic preferences that generated based on the taxonomic topic weighting approach in [8] to make item recommendations. However, the weighting approach in [8] did not consider the popularity of each taxonomic topic.

Our previous work [7] proposed a recommendation approach based on item taxonomy and folksonomy. It converted users' preferences on tags into users' preferences on taxonomic topics. Although the input information sources of this approach included both item taxonomy and folksonomy, it only used taxonomic topics to profile users' topic interests and did not use the folksonomy vocabulary and users' viewpoints on item classifications and descriptions.

This paper extends the existing work through exploring how to combine the two information sources that reflecting the opinions of users and experts on item classifications and descriptions to mine users' opinions on items and make personalized item recommendations.

III. NOTATIONS

In this paper, we focus on the top N item recommendation task. To describe the proposed approach, we define some key concepts used in this paper as below.

- **Users:** $U = \{u_1, u_2, \dots, u_{|U|}\}$ contains all users in an online community who have used tags to label and organize items.
- **Items (i.e., Products, Resources):** $P = \{p_1, p_2, \dots, p_{|P|}\}$ contains all items tagged by users in *U*. Items could be any type of resources or products in an online community such as web pages, videos, books, photos and papers etc.
- **Tags (i.e., Folksonomy):** $T = \{t_1, t_2, \dots, t_{|T|}\}$ contains all tags used by users in *U*. A tag is a piece of textural information given by one or more users to label or collect a set of items. Tags reflect the opinions of users on item classifications and descriptions.
- **Item Taxonomy:** $O =< C, R >, C = \{c_0, c_1, \dots, c_{|C|-1}\}$ is a set of taxonomic topics or categories given by experts to describe or classify items and R is a set of relations between any $c_x \in C$ and $c_y \in C$. Item taxonomic topics reflect the opinions of experts on item classifications and descriptions. In this paper, we only use the typical hierarchical relationship. We define $R = \{\prec\}$, $\prec$ is a "sub topic of" relationship, for any two topics c_x, $c_y \in C$, if $c_x \prec c_y$, then c_x is a sub topic of c_y. The taxonomy tree has exactly one root topic.
- **Item taxonomic descriptors:** Each item p_k is associated with a set of item taxonomic descriptors $D(p_k) = \{d_1, d_2, \dots, d_g\}$. A taxonomic descriptor is a sequence of ordered taxonomic topics, denoted by $d_i = \{c_0, c_y, c_x, \dots, c_a\}$, $c_0, c_y, c_x, \dots, c_a \in C$, c_0 is the root topic, c_a is a leaf topic, $c_a \prec \cdots \prec c_x \prec c_y \prec c_0$.
- **Features:** $F = \{\{c_0, c_1, \dots, c_{|C|-1}\}, \{t_1, t_2, \dots, t_{|T|}\}\}$, contains all the features that are used to describe items in *P*. In this paper, tags and taxonomic topics are used as features describing the items, which are called tag based features and taxonomic topic based features respectively.

Figure 1 (a) illustrates an example of tagging. For example, user u_4 has used the tag t_5 and tagged item p_5 and p_6. Figure 1 (b) shows an example of item taxonomy. Suppose p_1 is a book which is described by descriptor d_1, $D_{p_1} = \{d_1\}$, where $d_1 = \{c_0, c_1, c_4\}$. The book p_1 is described by taxonomic topics based features {"book", "garden", "flowers"} in the viewpoint of experts and tag based features {"garden", "apple"} in the opinion of user u_1.

IV. THE PROPOSED APPROACHES

The proposed approaches include two major tasks. The first task is to mine users' opinions on items. Then, based on users' opinions on items, a set of items will be recommended.

A. Opining mining

The opinion mining process includes the following three sub tasks. 1) finding the relationships between features with respect to each individual user's opinion and representing each tag based on the feature relationships for each user; 2) mining users opinions on the features for each item, based on all users' tagging and taxonomy information; 3) determining each user's opinion to each item feature.

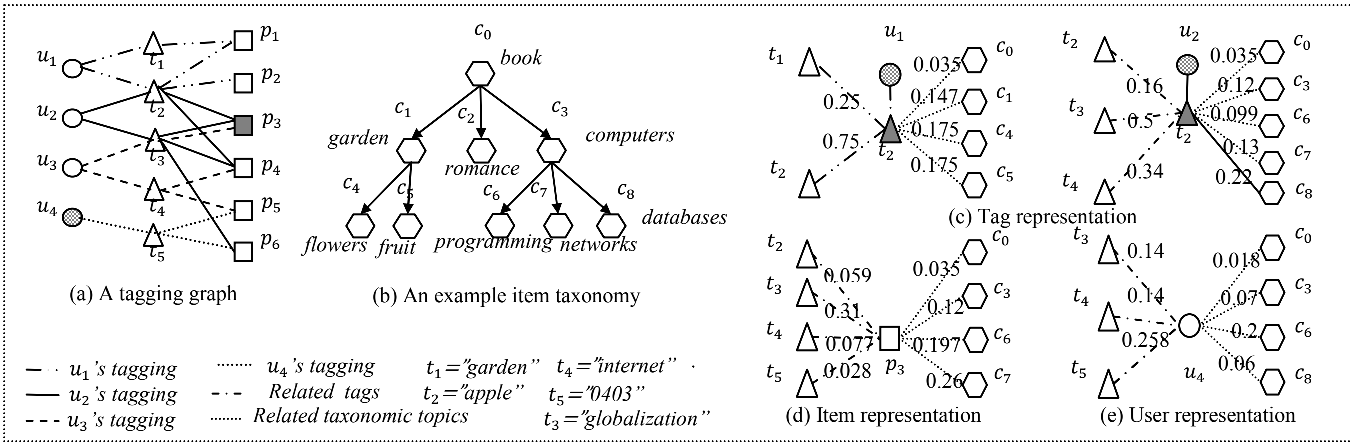

Figure 1. An example of tagging and representations.

1) Tag representation

How to find the relationship of features is a very important task for opinion mining [3]. Our purpose is to recommend those untagged or unrated items to each target user. Since the candidate items may be described by those very different features that are contributed by other users, if we can find the relationships among these features, we can estimate the target user's opinions to the candidate items. For example, in Figure 1, the user u_4 described the item with tag t_5 "0403". Assume p_3 is the candidate item. If we know the relevance of "0403" and the tag based and taxonomic topic based features of p_3, then we can estimate how much u_4 is interested in the item p_3.

Basically, the taxonomic topic based features contain structural relationship information. Besides the "sub" topic relationship, the "related" topic relationship also can be inferred. For example, although two taxonomic topics are different, if they have the same common ancestors, these topics are related. Tag based features don't have structural information. Usually, if two tags are used to describe the same item, then, these tags are closely related [5].

Another kind of important information that can be used to find the relationship of features is the personal tagging information. Tags are given by users to organize or describe their own items. It forms a three dimensional relationship User-Tag-Item among the three entities [6]. The User-Tag-Item relationship records the personal tagging information of each individual user [5]. In opinion of user u_i, the collected items under one tag are similar or closely related in some way, otherwise the user won't put them together and labeled them with the same tag. For example, in Figure 1 (a), with tag t_2, user u_1 collected p_1 and p_2 while user u_2 collected the p_3 and p_4. In u_1's opinion, p_1 and p_2 are more similar than other items, while in u_2's opinion, p_3 and p_4 are similar. Thus, the features of these items can be used to represent the conceptual categories covered by or related to the tag in terms of the user's opinion. The process of finding the relationships of features based on each individual user's opinion and representing each tag with the features is called tag representation, which is defined as below.

Definition 1 (Tag Representation): represents the relationships of features based on user u_i's opinion. Specifically, it represents tag $t_x \in T$'s relevance to each taxonomic topic based feature $c_y \in C$ and each tag based feature $t_z \in T$ in user u_i's opinion. Let $s_{u_i,t_x}(c_y)$ denote how strong t_x is related to c_y with respect to user u_i, the relationship between a tag and a set of taxonomic topics in the opinion of a user can be defined as the mapping $\mathcal{C}^t: U \times T \to 2^{C\times[0,1]}$, such that $\mathcal{C}^t(u_i,t_x) = \{(c_y, s_{u_i,t_x}(c_y)) \mid c_y \in C\}$. Let $r_{u_i,t_x}(t_z)$ denote how strong t_x is related to t_z with respect to user u_i, the relationship between a tag and a set of tags in the opinion of a user can be defined as the mapping $\mathcal{T}^t: U \times T \to 2^{T\times[0,1]}$, such that $\mathcal{T}^t(u_i,t_x) = \{(t_z, r_{u_i,t_x}(t_z)) \mid t_z \in T\}$. The tag representation of t_x with respect to user u_i is defined as $\mathcal{CT}^t(u_i,t_x) = \{\mathcal{C}^t(u_i,t_x), \mathcal{T}^t(u_i,t_x)\}$, $\mathcal{C}^t(u_i,t_x)$ reflects the opinion of experts on the classification of the collected items while $\mathcal{T}^t(u_i,t_x)$ reflects the opinions of users.

How to calculate the relevance weight of a tag to a taxonomic topic (i.e., $s_{u_i,t_x}(c_y)$) and the relevance weight between two tags (i.e., $r_{u_i,t_x}(c_y)$) based on the opinion of each individual user u_i is very important. For a given user u_i and a tag t_x, the strength of a taxonomic topic c_y being related to a tag t_x for the user u_i can be estimated based on the relevance weight of c_y to the items collected in the tag t_x of the user u_i. Let $h^p_{k,y}$ denote the relevance weight of taxonomic topic c_y to item p_k. The items in t_x of u_i is denoted as P_{u_i,t_x}, $P_{u_i,t_x} = \{p_{i1}, \dots, p_{in}\}$. We could use any of $h^p_{i1,y}, \dots, h^p_{in,y}$ to estimate the relevance of c_y to t_x for user u_i. Assuming that $h^p_{i1,y}, \dots, h^p_{in,y}$ are equally important to the user u_i to calculate the relevance of c_y to t_x, we use the average value of $h^p_{i1,y}, \dots, h^p_{in,y}$ to estimate the relevance of c_y to t_x. Let $s_{u_i,t_x}(c_y)$ denote the relevance weight of c_y and t_x in terms of u_i, it can be calculated as:

$$s_{u_i,t_x}(c_y) = \sum_{p_k \in P_{u_i,t_x}} \frac{h^p_{k,y}}{|P_{u_i,t_x}|} \qquad (1)$$

Each item p_k is associated with a set of item taxonomic descriptors D_{p_k} given by experts. Ziegler [8] proposed to decay the weight of the taxonomic topic node based on the number of children of the taxonomic topic node in the item taxonomy tree and the length of the descriptor. Let $f(c_y, d_j)$ denote the weight of topic c_y in descriptor $d_j \in D_{p_k}$ of item p_k. Suppose a descriptor $d_j = \{c_0, c_z, c_x, c_a\}$ and $c_a \prec c_x \prec c_z \prec c_0$, inspired by Ziegler's approach, we take the structural information of item taxonomy into consideration to calculate the weight $f(c_y, d_j)$ for c_y in d_j. For the non-leaf topic c_z in the example descriptor d_j given above, $f(c_z, d_j)$ can be calculated as:

$$f(c_z, d_j) = \frac{f(c_x, d_j)}{child(c_z)} \qquad (2)$$

Where c_z is the parent node of topic c_x in d_j, $child(c_z)$ is the number of child nodes of topic c_z. To facilitate comparison, the total weight of all the topics in d_j is equal to 1. Let x be the weight of the leaf node c_a of the example descriptor d_j, we get the following equation:

$$x + \frac{x}{child(c_x)} + \frac{x}{child(c_x) \cdot child(c_z)} + \frac{x}{child(c_x) \cdot child(c_z) \cdot child(c_0)} = 1 \quad (3)$$

After resolving (3), we can get the value of x (i.e.,$f(c_a, d_j)$). Based on the leaf node weight $f(c_a, d_j)$ and (2), we can get the weight of each non-leaf topic in d_j. Apparently, the leaf nodes have higher weight values than those of non-leaf nodes now. However, if a topic is popularly used to describe items, it is not a distinctive topic to represent this item. Similar to the *idf* weighting approach in text mining, we should consider the popularity of a topic for all items. Let $iif(c_y)$ denote the inverse item frequency of topic c_y, usually, $iif(c_y) = |P|/log(|P_{c_y}|)$, where $|P_{c_y}|$ is the number of items that have been described with c_y in the item set P. To get a value between 0 and 1 to facilitate comparison, we set $iif(c_y) = 1/log(e + |P_{c_y}|)$, where e is an irrational constant approximately equal to 2.72 and $0 < iif(c_y) \leq 1$. Assuming each descriptor is equally important for the topic classification of item p_k, we use the average value of $f(c_y, d_j)$ in D_{p_k} to measure the relevance weight of item p_k to the topic c_y. Let $|D_{p_k}|$ denotes the number of descriptors of item p_k, the relevance weight $h^p_{k,y}$ can be calculated as:

$$h^p_{k,y} = \frac{1}{|D_{p_k}|} \sum_{d_j \in D_{p_k}} f(c_y, d_j) \cdot iif(c_y) \qquad (4)$$

For a given user u_i and a tag t_x, the strength of a tag t_z being related to the tag t_x for the user u_i can be estimated based on the probabilities of t_z being used to tag the items collected in the tag t_x of the user u_i [5]. Let $|U_{p_k,t_x}|$ be the number of users tagged p_k with t_z, $|U_{p_k}|$ is the number of users that have tagged item p_k, the conditional probability of t_z being used to tag item p_k, given the item p_k denoted as $\mathcal{P}r(t_z \mid p_k)$ can be calculated as:

$$\mathcal{P}r(t_z \mid p_k) = \frac{|U_{p_k,t_z}|}{|U_{p_k}|} \qquad (5)$$

Let $r_{u_i,t_x}(t_z)$ denote the relevance of a tag t_x to a tag t_z for user u_i, it can be calculated as:

$$r_{u_i,t_x}(t_z) = \sum_{p_k \in P_{u_i,t_x}} \frac{\mathcal{P}r(t_z \mid p_k)}{|P_{u_i,t_x}|} \qquad (6)$$

Example 1 (Tag Representation) The descriptors of the items in Figure 1 (a) are defined as: $D_{p_1} = \{d_1\}, D_{p_2} = \{d_2\}$, $D_{p_3} = \{d_3, d_4\}$, $D_{p_4} = \{d_5\}$, $D_{p_5} = \{d_3\}$, $D_{p_6} = \{d_3, d_5\}$, where $d_1 = \{c_0, c_1, c_4\}$, $d_2 = \{c_0, c_1, c_5\}$, $d_3 = \{c_0, c_3, c_6\}$, $d_4 = \{c_0, c_3, c_7\}$, $d_5 = \{c_0, c_3, c_8\}$. Figure 1 (c) shows an example of the tag representations of tag t_2 for u_1 and u_2.

The calculation of the relevance of tag t_2 and c_6 for u_2 is shown as follows: since u_2 collected item p_3 and p_4 with tag t_2, $s_{u_2,t_2}(c_6) = \sum_{p_k \in P_{u_2,t_2}} \frac{h^p_{k,6}}{|P_{u_2,t_2}|} = \frac{h^p_{3,6} + h^p_{4,6}}{2}$. There are two descriptors d_3 and d_4 for item p_3, $h^p_{3,6} = \frac{1}{|D_{p_3}|} \sum_{d_j \in D_{p_3}} f(c_6, d_j) \cdot iif(c_6) = \frac{1}{2} \cdot (f(c_6, d_3) + f(c_6, d_4)) \cdot iif(c_6)$. Show in Figure 1 (b), $child(c_3) = 3, child(c_0) = 3$. Suppose $f(c_6, d_3) = x$, $x + \frac{x}{3} + \frac{x}{3 \cdot 3} = 1$, $x = 0.69$. Similarly, $f(c_6, d_4) = 0$. Since c_6 has described p_3, p_5 and p_6, $iif(c_6) = \frac{1}{log(e+3)}$=0.57. Thus, $h^p_{3,6} = \frac{1}{2} \cdot (0.69 + 0) \cdot 0.57 = 0.197$, $h^p_{4,6}$ =0, $s_{u_2,t_2}(c_6)$=0.099. The relevance of t_2 and t_3 for u_2 can be calculated as: $r_{u_2,t_2}(t_3) = \sum_{p_k \in P_{u_2,t_2}} \frac{\mathcal{P}r(t_3 \mid p_k)}{|P_{u_2,t_2}|} = \frac{\mathcal{P}r(t_3 \mid p_3) + \mathcal{P}r(t_3 \mid p_4)}{2} = \frac{1}{2} \cdot \frac{2}{3} + \frac{1}{2} \cdot \frac{1}{3} = 0.5$. Similarly, $s_{u_1,t_2}(c_6) = 0$, $r_{u_1,t_2}(t_3)$=0.

For user u_1, the tag t_2 "apple" is mainly related to c_1 "garden", c_4 "flowers" and c_5 "fruit". While for user u_2, it mainly related to c_3 "computers", c_6 "programming", c_7 "networks" and c_8 "databases". In the folksonomy, t_2 is related to t_1 "garden" for user u_1, while t_2 is related to t_3 "globalization" and t_4 "internet" for u_2.

Therefore, the relationships of features based on each individual user's opinion are obtained. Based on the tag representations, we can find more accurate item descriptions or classifications and users' opinion on the features, which will be discussed as follows.

2) Item representation

How to incorporate users' opinions to rank, organize and classify items is another important task [3].Typically, items are classified by experts and described with taxonomic topic based features. In Web 2.0, users use tags to express their own opinions on item classifications and descriptions. How to classify items and describe each item with related features based on all users' opinions and experts' viewpoint is the major focus of this subsection. The process of determining the related features of each item and represent each item with the features is called item representation.

Definition 2 (Item Representation): represents the relationships between item p_k and the features based on the opinions of users and experts. Specifically, for each item $p_k \in P$, it represents the item p_k's relevance to each taxonomic topic based feature $c_y \in C$ and each tag based feature $t_z \in T$. Let $h^p_{k,y}$ denote the weight of how much the item p_k is relevant to the taxonomic topic c_y, the relationship between an item and a set of taxonomic topics can be defined as the mapping $\mathcal{C}^p: P \rightarrow 2^{C\times[0,1]}$, such that $\mathcal{C}^p(p_k) = \{(c_y, h^p_{k,y}) | c_y \in C\}$. Let $w^p_{k,z}$ denote the weight of how much the item p_k is relevant to the tag t_z, the relationship between an item and a set of tags can be defined as the mapping $\mathcal{T}^p: P \rightarrow 2^{T\times[0,1]}$, such that, $\mathcal{T}^p(p_k) = \{(t_z, w^p_{k,z}) | t_z \in T\}$. The item representation of p_k is defined as $\mathcal{CT}^p(p_k) = \{\mathcal{C}^p(p_k), \mathcal{T}^p(p_k)\}$, $\mathcal{C}^p(p_k)$ reflects the opinion of experts while $\mathcal{T}^p(p_k)$ reflects the opinion of users.

Based on (4), we can calculate how much item p_k is relevant to taxonomic topic c_y. Mainly, we discuss how to measure the relevance weight $w^p_{k,z}$ of item p_k to a tag t_z in this sub section. As discussed in the above sub section, the weight $r_{u_i,t_x}(t_z)$ estimates the relevance of a tag t_z to a tag t_x with respect to a user u_i. Since the items collected in t_x must have something in common (otherwise the user will not put them together in one tag), the related tag t_z should reflect some topics of the items in t_x. As discussed in [5], the relevance weight $w^p_{k,z}$ of item p_k to a tag t_z can be calculated as:

$$w^p_{k,z} = \sum_{u_i \in U_{p_k}, t_x \in T_{p_k}} \frac{1}{\mathrm{M}} \cdot r_{u_i,t_x}(t_z) \cdot iif(t_z) \qquad (7)$$

Where $iif(t_z)$ is the inverse item frequency of tag t_z, T_{p_k} is the tag set of p_k, U_{p_k} is the user set of p_k, and M is the number of unique user-tag (u_i, t_x) pairs of item p_k.

Since the two mappings $\mathcal{C}^p(p_k)$ and $\mathcal{T}^p(p_k)$ can be viewed as two value vectors: $\mathcal{C}^p(p_k) =< h^p_{k,0}, \dots, h^p_{k,|C|-1} >$ for topics $< c_0, \dots, c_{|C|-1} >$, $\mathcal{T}^p(p_k) =< w^p_{k,1}, \dots, w^p_{k,|T|} >$ for tags $<t_1, \dots, t_{|T|}>$, each item p_k can be described by a $|C|$-sized taxonomic topic value vector $\mathcal{C}^p(p_k)$ and a $|T|$-sized tag value vector $\mathcal{T}^p(p_k)$. The values can be calculated by (4) and (7) respectively.

Example 2 (Item Representation) The item representation of p_3 is shown in Figure 1 (d). With the calculation process shown in Example 1, the relevance value of item p_3 with taxonomic topics can be calculated. The calculation of the relevance of item p_3 to tag t_5 is shown as follows. Shown in Figure 1 (a), the user-tag pairs of item p_3 include (u_2, t_2), (u_2, t_3) and (u_3, t_3). $w^p_{3,5} = \sum_{u_i \in U_{p_3}, t_x \in T_{p_3}} \frac{1}{3} \cdot r_{u_i,t_x}(t_5) \cdot iif(t_5) = \frac{1}{3} \cdot (r_{u_2,t_2}(t_5) + r_{u_2,t_3}(t_5) + r_{u_3,t_3}(t_5)) \cdot iif(t_5)$. $r_{u_2,t_2}(t_5)=0$, $r_{u_2,t_3}(t_5)=\frac{1}{3}\cdot\frac{1}{2}$, $r_{u_3,t_3}(t_5)=0$. After the representations of items, p_5, p_6, p_3 and p_4 are relevant to t_5, $iif(t_5)=0.52$. $w^p_{3,5} = \frac{1}{3}\cdot\frac{1}{3}\cdot\frac{1}{2}\cdot 0.52 = 0.028$. Mainly, item p_3 related to c_3 "computers", c_6 "programming" and c_7 "networks" and tags t_3 "globalization" and t_4 "internet".

3) User profiling

User profile is used to describe a user's information such as interests, preferences, behavior and opinion [1]. Profiling each user's opinions to items is crucial for the prediction of whether a user will be interested in a candidate item. Not only the items that a user has tagged or collected, but also the opinions of the user to the collected items should be profiled. Thus, we propose to use both the item set of each user and the user's opinions on the classifications of these items to profile each user. The process of finding each user's opinion on item classifications and represent each user with the features of items is called user representation.

Definition 3 (User representation): represents user u_i's opinion on the features of items. Specifically, for each user $u_i \in U$, it represents the user u_i's preferences to each taxonomic topic based feature $c_y \in C$ and each tag based feature $t_z \in T$. Let $h^u_{i,y}$ denote the weight of how much the user u_i is interested in the taxonomic topic c_y, the relationship between a user and a set of taxonomic topics can be defined as the mapping $\mathcal{C}^u: U \rightarrow 2^{C\times[0,1]}$, such that $\mathcal{C}^u(u_i) = \{(c_y, h^u_{i,y}) | c_y \in C\}$. Let $w^u_{i,z}$ denote the weight of how much the user u_i is interested in the tag t_z, the relationship between a user and a set of tags can be defined as the mapping $\mathcal{T}^u: U \rightarrow 2^{T\times[0,1]}$. Such that $\mathcal{T}^u(u_i) = \{(t_z, w^u_{i,z}) | t_z \in T\}$. The user representation of u_i is defined as $\mathcal{CT}^u(u_i) = \{\mathcal{C}^u(u_i), \mathcal{T}^u(u_i)\}$.

How to obtain each user's preferences on the features is the major focus of this sub section. To calculate how much u_i will be interested in taxonomic topic c_y and tag t_z, we firstly calculate how much the user is interested in the tag t_x.

As discussed in [5], the strength of u_i will be interested in tag t_x can be calculated as $(t_x \mid u_i) = \frac{|P_{u_i,t_x}|}{|P_{u_i}|}$, where $|P_{u_i}|$ is the number of items that user $u_i$has tagged. For a given user u_i and a tag t_x, based on (1), we can get the relevance weight $s_{u_i,t_x}(c_y)$ between tag t_x and taxonomic topic c_y for user u_i. Thus, we can estimate each user u_i's preferences to the taxonomic topic c_y through calculating the product of $s_{u_i,t_x}(c_y)$ and $\mathcal{Pr}(t_x \mid u_i)$. Let $iuf(c_y)$ denote as the inverse user frequency of topic c_y, the weight $h^u_{i,y}$ can be calculated as:

$$h^u_{i,y} = \sum_{t_x \in T} \mathcal{Pr}(t_x \mid u_i) \cdot s_{u_i,t_x}(c_y) \cdot iuf(c_y) \quad (8)$$

Let $iuf(t_z)$ denote the inverse user frequency of tag t_z, the weight $w^u_{i,z}$ can be calculated as:

$$w^u_{i,z} = \sum_{t_x \in T} \mathcal{Pr}(t_x \mid u_i) \cdot r_{u_i,t_x}(t_z) \cdot iuf(t_z) \quad (9)$$

The two mappings $\mathcal{C}^u(u_i)$ and $\mathcal{T}^u(u_i)$ can be viewed as two value vectors: $\mathcal{C}^u(u_i) =< h^u_{k,0}, \dots, h^u_{k,|C|-1} >$ for topics $< c_0, \dots, c_{|C|-1} >$, $\mathcal{T}^u(u_i) =< w^u_{k,1}, \dots, w^u_{k,|T|} >$ for tags $<t_1, \dots, t_{|T|}>$. We profile each user u_i with item and feature preferences. Thus, each user u_i can be profiled by three vectors: u^P_i, $\mathcal{C}^u(u_i)$ and $\mathcal{T}^u(u_i)$. u^P_i is a $|P|$-sized binary item vector representing u_i's collected item set. If u_i has item p_k, then the value of this item in vector u^P_i is 1, otherwise is 0. $\mathcal{C}^u(u_i)$ is a $|C|$-sized taxonomic topic value vector and $\mathcal{T}^u(u_i)$ is a $|T|$-sized tag value vector.

Example 3 (User Representation) The user representation of u_4 is shown in Figure 1 (e). The calculation of u_4's preferences to taxonomic topic c_6 "programming" is shown as follows: $h^u_{4,6} = \sum_{t_x \in T} \mathcal{Pr}(t_x \mid u_4) \cdot s_{u_4,t_x}(c_6) \cdot iuf(c_6) = \mathcal{Pr}(t_5 \mid u_4) \cdot s_{u_4,t_5}(c_6) \cdot iuf(c_6)$. Based on the tagging graph in Figure 1 (a), we can get $\mathcal{Pr}(t_5 \mid u_4) = 1$. $iuf(c_6) = 0.57$, $s_{u_4,t_5}(c_6) = 0.32$. Thus, $h^u_{4,6} = 1 \cdot 0.32 \cdot 0.57 = 0.2$. The calculation of u_4's preferences to tag t_4 "internet" is shown as follows. $w^u_{4,4} = \sum_{t_x \in T} \mathcal{Pr}(t_x \mid u_4) \cdot$

$r_{u_4,t_x}(t_4) \cdot iuf(t_4) = \mathcal{P}r(t_5 \mid u_4) \cdot r_{u_4,t_5}(t_4) \cdot iuf(t_4)$. After user representations, u_3, u_2 and u_4 have preferences on t_4 , $iuf(t_4)$ =0.57. Thus, $w^u_{4,4} = 1 \cdot \left(\frac{1}{2} \cdot \frac{1}{2}\right) \cdot 0.57$ =0.14. Shown in Figure 1 (e), although u_4 used a personal tag t_5 "0403" to collect items, we can find that u_4 also interested in topics c_6 "programming" and c_3 "computers". In the folksonomy of this user community, u_4 is also interested in tag t_3 "globalization" and t_4 "internet".

Therefore, each user and item is represented with a set of taxonomic topics and tags. Since memory based CF approaches are more popularly used for implicit ratings and other user behaviors, based on user and item representations, the memory based CF and content mapping can be used to form neighborhood and recommend items.

B. Personalized Item Recommendation making

How to recommend items based on the users' opinions is another important research question [6]. With users' opinion information, not only the similarity of the objective content information of items, but also the similarity of users' opinions to these items will affect whether an item will be considered as similar to another item. Moreover, both the similarity of the collected item sets and the similarity of users' opinions to the features of items will be considered to determine whether a user is a peer neighbor user to another user. Thus, users' opinion information will affect whether an item will be recommended to a target user. After incorporating users' opinion information, different neighborhood will be formed and the rank of the recommended items will be different. We discuss the neighborhood forming and recommendation generation approaches in the following sub sections.

1) Neighborhood Forming

Neighborhood formation is to generate a set of like-minded peers for a target user $u_i \in U$ or a set of similar peer items for an item $p_i \in P$. The more accurate a user profile or item representation is, the more similar neighbor users or items will be found. We use cosine similarity to measure the similarity of any two taxonomic topic value vectors as well as any two tag value vectors.

The similarity of two users u_i and u_j includes two parts: the similarity of items and the similarity of features. The feature preferences are represented by taxonomic topic value vector and tag value vector, we linearly combine the similarities of them to measure the similarity of topic preferences. Since the approach of weighting each commonly rated item with its inversed user frequency or *iuf* [9] performs better for binary ratings in many cases [9], we use this *iuf* approach to calculate the similarity of items of two users denoted as $sim^P_u(u_i, u_j)$.

$$sim^P_u(u_i, u_j) = \frac{\sum_{p_k \in P_{u_i} \cap P_{u_j}} iuf(p_k)}{\sqrt{|P_{u_i}| \cdot |P_{u_j}|}} \quad (10)$$

Where $|P_{u_i}|$ is the number of items that u_i has tagged. Thus, the similarity of two users is defined as below:

$$sim_u(u_i, u_j) = \lambda_1 \cdot sim^P_u(u_i, u_j) + (\lambda_2 \cdot cos\left(\mathcal{C}^u(u_i), \mathcal{C}^u(u_j)\right) + \lambda_3 \cdot cos\left(\mathcal{T}^u(u_i), \mathcal{T}^u(u_j)\right)) \quad (11)$$

Where $0 \le \lambda_1, \lambda_2, \lambda_3 \le 1$ and $0 \le \lambda_1 + \lambda_2 + \lambda_3 \le 1$. Similarly, the similarity of two items can be calculated as:

$$sim_p(p_i, p_j) = \eta \cdot cos\left(\mathcal{C}^p(p_i), \mathcal{C}^p(p_j)\right) + (1-\eta) \cdot cos\left(\mathcal{T}^p(p_i), \mathcal{T}^p(p_j)\right) \quad (12)$$

Where $0 \le \eta \le 1$. The *K* nearest neighbor users who have similar user profiles with u_i can be found, which is denoted as $\check{N}(u_i)$.

2) Recommendation Generation

A set of items that are most frequently tagged by the neighbors of the target user or most similar to the target user's items will be recommended to the target user. The similarity of taxonomic topics and tags between the target user and the candidate item can be used to improve the accuracy of recommendations through selecting those items that are not only tagged by the most similar users, but also have similar taxonomic topics and tags with the target user. We discuss both user and item based CF approaches that combine the topic mapping respectively.

4.5.1 User based approach

For each target user u_i, a set of candidate items will be generated from the items tagged by u_i's neighbourhood formed based on the similarity of user profiles. For each candidate item p_k, the prediction score of how much u_i may be interested in p_k is calculated in terms of the aspects of how similar those users who have the item p_k and how similar the item's features with u_i's feature preferences. We use the simple linear combination to hybrid the two parts. Similarly, we linearly combine the feature match of both taxonomic topics and tags. For each candidate item p_k, the prediction score can be calculated as:

$$\mathcal{A}_u(u_i, p_k) = \sum_{u_j \in \check{N}(u_i) \cap U_{p_k}} (\alpha_1 \cdot sim_u(u_i, u_j) + (\alpha_2 \cdot cos(\mathcal{C}^u(u_i), \mathcal{C}^p(p_k)) + \alpha_3 \cdot cos(\mathcal{T}^u(u_i), \mathcal{T}^p(p_k)))) \quad (13)$$

Where $0 \le \alpha_1, \alpha_2, \alpha_3 \le 1$ and $0 \le \alpha_1 + \alpha_2 + \alpha_3 \le 1$.

4.5.2 Item based approach

For item based approach, the candidate item set can be the whole item set except those items that are already rated/tagged by the target user. To avoid unnecessary computation of item pairs, the top *K* most similar items of each tagged item of the target user u_i can be aggregated together as the candidate item set. For each candidate item p_k , we propose to calculate the prediction score of a candidate item based on the maximum score of the linear combination of the similarity with each tagged item and the similarity with the target user's feature preferences. Similarly, we linearly combine the feature match of both taxonomic topics and tags. The prediction score for each candidate item p_k can be calculated as:

$$\mathcal{A}_p(u_i, p_k) = max_{p_y \in P_{u_i}} \{\beta_1 \cdot sim_p(p_y, p_k) + (\beta_2 \cdot cos(\mathcal{C}^u(u_i), \mathcal{C}^p(p_k)) + \beta_3 \cdot cos(\mathcal{T}^u(u_i), \mathcal{T}^p(p_k)))\} \quad (14)$$

Where $0 \le \beta_1, \beta_2, \beta_3 \le 1$ and $0 \le \beta_1 + \beta_2 + \beta_3 \le 1$.

V. EXPERIMENT DESIGN

A. Data preparation

We conducted the experiments with two real world datasets that from Amazon.com and CiteULike.com. The former dataset has taxonomy and folksonomy information while the latter one only has folksonomy information.

1) Dataset D1: Amazon.com dataset. This dataset was crawled from Amazon.com on April, 2008. The items of the dataset are books. To avoid too sparse, we only select those users that have at least 5 items and those items that have been used by at least 3 users. The final dataset consists of 4112 users, 34201 tags, 30467 items. We also extracted the taxonomic descriptors [7] of each item from amazon.com. The taxonomy contains 9919 unique topics.

2) Dataset D2: CiteULike dataset. The "Who-posted-what" dataset (http://static.citeulike.org/data/current.bz2) is used. The items are research papers. We select those users that have at least 5 items and those items that have been used by at least 2 users. The final dataset comprises 7103 users, 78414 tags, 117279 items.

B. Experiments setup

To evaluate the proposed approaches, each dataset was 5 folded and split into 5 datasets. For each split dataset, 80% of users were used as the training users while 20% of users were randomly selected as the test users. For each test user, randomly, 20% of the items of this user were hidden as the test/answer set while 80% of each user's items are used as his/her training set. The training set of each user contains user's items and corresponding tags information as well. For each test user, the recommender system will generate a list of ordered items that the test user didn't collect. The top N items with high prediction scores will be recommended to the user. If an item in the recommendation list was in the test user's hidden item list, then the item was counted as a hit. The average precision and recall of the whole test users of one split dataset were recorded as one run of the results. The average precision and recall values of the 5 split datasets were used to measure the accuracy of the recommendations.

VI. RESULTS AND DISCUSSIONS

In this section, we firstly discuss the setting of the parameters. Then, we discuss the influences of folksonomy and taxonomy that to the accuracy of recommendations and the comparison of the proposed approaches with other related state-of-art work.

A. The setting of Parameters

The results indicated that with $\lambda_1 = 0.8$, $\lambda_2 = 0.1$, $\lambda_3 = 0.1$, $\alpha_1 = 0.3$, $\alpha_2 = 0.2$, $\alpha_3 = 0.5$, the proposed user based approach achieved the best performances for Dataset D1. With $\eta = 0.3$, $\beta_1 = 0.3$, $\beta_2 = 0.2$, $\beta_3 = 0.5$, the proposed item based approach achieved the best performances for Dataset D1. Since there is no taxonomy information for Dataset D2, the values of λ_2, α_2, η, and β_2 were set to 0. The results suggested that with $\lambda_1 = 0.9$, $\lambda_3 = 0.1$, $\alpha_1 = 0.4$, and $\alpha_3 = 0.6$, the proposed user based approach achieved the best performances for Dataset D2. With $\beta_1 = 0.4$ and $\beta_3 = 0.6$, the proposed item based approach achieved the best performances for Dataset D2. The following discussions are given on the basis of the best settings of the parameters.

B. Taxonomy V.S. Folksonomy

To measure the influences of taxonomy and folksonomy for the improvement of the recommendation accuracy, we compared the top 3 (N=1,…,3) recommendation precision values of the proposed approaches that represent the topic preferences of each user and topics of each item using both taxonomic topics and tags with the approaches that represent users or items using taxonomic topics or tags only. We also compared the proposed approaches with the approach proposed by Ziegler [8]. The following are the 5 approaches compared in this part of experiments.

- ***CTR-User*** and ***CTR-Item***: These are the proposed user and item based approaches that represent each user and item with both taxonomic topics and tags. For simplicity, they are called the combined models.
- ***CR-User*** and ***TR-User***: *CR-User* is the proposed user based approach that only represents each user and item with taxonomic topics while tags are used for *TR-User*. *CR-User* is called taxonomy model. *TR-User* is called folksonomy model.
- ***TPR:*** Ziegler proposed an approach to acquire a user's topic preferences based on item taxonomic topics [8]. For a fair comparison, *TPR* combined item preferences and topic preferences generated based on [8].

The top 3 precision values are shown in Figure 2.

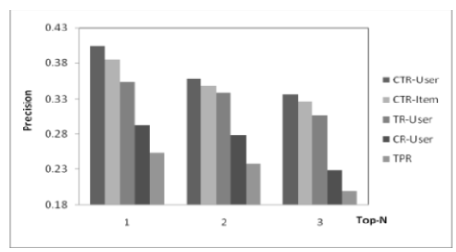

Figure 2. Top 3 Precision values of Dataset D1.

Discussions:

As shown in Figure 2, the proposed user based approach *CTR-User* performed slightly better than the proposed item based approach *CTR-Item.* Both the combined models performed better than the proposed taxonomy model *CR-User* and folksonomy model *TR-User.* For example, the Top-1 (N=1) precision value of *CTR-User* was 0.41, while that of *TR-User* was 0.35 and that of *CR-User* was 0.29. It indicated that after combining the item taxonomy and folksonomy information, the accuracy of item recommendations can be further improved. Moreover, the proposed taxonomy model *CR-User* performed better than *TPR* that is based on the weighing approach proposed in [8]. The improvement suggested that after considering both structural information and the popularity of taxonomic topics, the recommendation accuracy based on item taxonomy can be improved.

Another important finding is that the proposed folksonomy model *TR-User* performed much better than the proposed taxonomy model *CR-User*. To further discuss the proposed folksonomy and taxonomy model, we select a set of tags whose popularity are larger than or equal to θ, and only retained those selected tags in the user and item representations. Then, we compared the Top-3 (N=3) precision values for the two models. The number of tags used by at least θ users of both datasets and the Top-3 precision values of the proposed folksonomy model with different θ values are plotted in Figure 3 where θ was set from 1 to 10 incrementally.

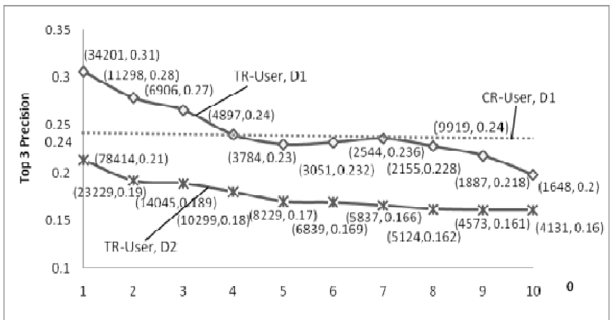

Figure 3. The number of tags used by at least θ users and the Top-3 (N=3) Precision results with different θ values.

As shown in Figure 3, with θ=1, we retained all the tags (i.e., 34201) in the item and user representations and got the best precision value 0.31 for Dataset D1 with the proposed folksonomy model *TR-User*. Similarly, the best precision value can be achieved for Dataset D2 with the proposed *TR-User* approach when we retain all the tags (i.e., 78414). The distributions of tags follow the power law distributions [3]. Figure 3 indicated that although keeping more tags not necessarily improved the precision values, the precision values decreased dramatically when a large number (i.e., 90%) of tags with lower θ values (i.e., $\theta \leq 5$) was removed.

We compared the proposed folksonomy model *TR-User* with the proposed taxonomy model *CR-User* on Dataset D1. The Top-3 (N=3) precision value for the proposed taxonomy model was 0.24 and there were 9919 unique taxonomic topics in the dataset D1. As shown in Figure 3, only when we selected less than 4897 tags with $\theta > 4$, the proposed folksonomy model performed worse than the taxonomy model (i.e., $\leq$0.24). It suggested that after making use of the rich opinion information, folksonomy can be used as quality information source to provide more accurate personalized item recommendations than taxonomy.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed to integrate the item taxonomy and folksonomy information to conduct opinion mining and make personalized item recommendations. The item and user based CF combining with the content filtering approaches are presented. The experimental results show that the proposed approaches are effective. The best performances of the proposed combined approaches suggest that integrating the standard item taxonomy vocabulary and experts' viewpoint on item descriptions/classifications with users' personal vocabularies and viewpoints can further improve the accuracy of item recommendations. The future work will explore how to integrate tags with other types of user opinion information such as reviews, blogs, and micro blogs such as tweets to find users' opinions on items and make better personalized item recommendations.

REFERENCES

[1] Adomavicius, G., and Tuzhilin, A., Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6):2005, 734-749.

[2] Eda, T., Yoshikawa, M., Uchiyama, T., and Uchiyama, T., The Effectiveness of Latent Semantic Analysis for Building Up a Bottom-up Taxonomy from Folksonomy Tags. In Proc. of WWW'09, 421 – 440.

[3] Pang, B., and Lee L., Opinion Mining and Sentiment Analysis, Foundations and Trends in Information Retrieval. Vol. 2: No 1–2, 2008, 1-135.

[4] Sen, S., Lam, S., Rashid, A., Cosley, D., Frankowski, D., Osterhouse, J., Harper, M., and Riedl., J., Tagging, communities, vocabulary, evolution. In Proc. of CSCW '06, 181-190.

[5] Liang, H., Xu, Y., Li, Y., and Nayak, R., Connecting users and items with weighted tags for personalized item recommendations. In Proc. of HT'10, 51-60.

[6] Milicevic, A. K., Nanopoulos, A., and Ivanovic, M., Social tagging in recommender systems: a survey of the state-of-the-art and possible extensions. Artificial Intelligence Review. Springer Netherlands, 2010, 187-209.

[7] Liang, H., Xu, Y., Li, Y., and Nayak, R., Weng, L., Personalized Recommender Systems Integrating Social tags and Item Taxonomy. In Proc. of WI'09, 540-547.

[8] Ziegler, C.N., Lausen, G.& Schmidt-Thieme, L., Taxonomy-driven Computation of Product Recommendations. In Proc. of CIKM 2004, 406-415.

[9] Breese, J.S., Heckerman, D., and Kadie, C., Empirical Analysis of Predictive Algorithms for Collaborative Filtering. In Proc. of Conference on Uncertainty in Artificial Intelligence, 2008, 43-52.

[10] Jakob, N., Weber, S., Müller, M., Gurevych, I., Beyond the Stars: Exploiting Free-Text User Reviews for Improving the Accuracy of Movie Recommendations, In Proc. of TSA'09, 57-64.

[11] Mei, Q., Ling, X., Wondra, M., Su, H., Zhai, C., Topic sentiment mixture: modeling facets and opinions in weblogs. In Proc. of WWW'07, 171 - 180

[12] The Library of Congress, http://www.loc.gov/.

[13] Titov, I., and McDonald, R., Modeling online reviews with multi-grain topic models. In proc. of the WWW'08, 111-120.

[14] Liu., B., Sentiment Analysis and Subjectivity. Handbook of Natural Language Processing, Second Edition, (editors: N. Indurkhya and F. J. Damerau), 2010.

[15] Bindelli, S., Criscione, C., Curino, C., Drago, M.L., Eynard, D., Orsi, G., Improving Search and Navigation by Combining Ontologies and Social Tags. In Proc. of OTM Workshops 2008, 76-85.

[16] Rendle, S., Marinho, L.B., Nanopoulos, A., Schmidt-Thieme, L., Learning optimal ranking with tensor factorization for tag recommendation. In Proc. of KDD'09, 727-736.

[17] Weng, L.-T., Xu, Y., Li, Y. and Nayak, R., Web Information Recommendation Making based on Item Taxonomy. In Proc. of ICEIS'08, 20-28.

[18] Burke, R., Hybrid Recommender Systems: Survey and Experiments. User Modeling and User-Adapted Interaction, 12(2002), 331-370.